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Pre-processing rainfall data from multiple gauges to improve TOPMODEL simulation results in a large semi-arid region

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Abstract:

Modelling of semi-arid regions presents some complex challenges that must be overcome to produce reliable simulation results. This paper discusses the findings of a calibration and cross-validation process using TOPMODEL to simulate stream discharge from the semi-arid Banqiao sub-catchment located in Gansu Province, China. Rainfall was pre-processed using two different methods and compared against the use of mean rainfall data from 10 gauging stations. The results indicate that correlating multiple rainfall gauge measurements against stream discharge and weighting the rainfall gauges according to correlation factors can be a useful means of obtaining more representative rainfall input. The second method used a transfer function model (TFM) equipped with a non-linear rainfall filter function to generate effective rainfall. The TFM was calibrated repeatedly using different degrees of non-linearity in the rainfall filter function until an optimal model was found. The effective rainfall used to generate the best TFM was applied in TOPMODEL. Applying the TFM effective rainfall to TOPMODEL allowed better simulation of discharge than use of either the correlation-weighted or mean rainfall input. Although the R^2 validation efficiencies or 'goodness of fit' generally lagged those seen during calibration, 90% of TOPMODEL validation runs using TFM effective rainfall and 60% of those using correlation-weighted rainfall exceeded runs using mean rainfall. Copyright © 2004 John Wiley & Sons, Ltd.

KEY WORDS TOPMODEL; semi-arid region; multiple gauges; rainfall; pre-processing

INTRODUCTION

In recent decades, China has undergone a rapid increase in urbanization and industrialization that has significantly impacted environmental and hydrological processes there. These human influences have been magnified by China's high population density and uneven water distribution. Approximately 80% of China's available water supply is located in southern China and 60% of the annual precipitation in that region falls between April and July. In the north, with only 20% of the country's water, 80% of precipitation occurs between July and September, making water shortage one of northern China's most critical issues (Wang *et al.*, 1999). Many believe that improvements to this situation may come from the development of a framework for sustainable, integrated water resources management (e.g. see Liu and Xia (2004)).

As a small step toward this end, this paper investigates the application of a relatively simple, topographically based, hydrological model, i.e. TOPMODEL, developed by Beven *et al.* (1995), to a semi-arid region of China's northern province of Gansu. The Banqiao sub-catchment is a 730 km^2 branch of the Malianhe watershed located at approximately 36 °N and 108 °E. The Malianhe watershed contributes to the Jinghe, a tributary of the Yellow River, one of China's two most important waterways.

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The Banqiao sub-catchment was selected for this study because of the availability of hydrological and topographic elevation data prepared during previous research by Wang (2001). This catchment is also of interest because of its similarity to many other catchments in the north and west of China.

Representative precipitation

Only a limited number of successful applications of TOPMODEL in dry catchments were noted by Beven (2001), which he attributed to the model's inherent suitability for simulating the quick response from saturated contributing areas in wetter regions. The experience of Quinn *et al*. (1991) demonstrated that TOPMODEL only provided satisfactory results once the model had reached a 'wetted up' state after initial dry conditions. But, as Beven (2001) pointed out, dry catchments may never reach this state.

As noted by Durand *et al*. (1992), under parched conditions, soils with high organic matter content showed hydrophobic characteristics that resulted in 'imperfect wetting' and 'short circuiting' of the majority of the root zone. Such phenomena produced sharp peaks in the observed hydrograph. Parkes (personal communication, 2001) has also suggested that a 'baked' surface crust could inhibit soil penetration, resulting in similar sharp-peaked hydrographs. He also noted that some soils in northern China exhibit 'pipe-flow-like' subsurface flow patterns. Water flows via the path of least resistance through faults in the soil structure, rather than infiltrating uniformly through the profile, thus producing rapid response hydrographs.

This study demonstrated that adequate spatial representation of rainfall within the catchment is a determining factor in successfully simulating river discharge. As reported by Melching (1995) methods implemented in the generation of meaningful, representative rainfall data sets, from point precipitation measurements, are significant sources of uncertainty. Counted among these uncertainties are spatial and temporal variability of rainfall, sensitivity of gauge locations, measurement and synchronization errors and aeral-mean rainfall representation. When models are calibrated using data sets that contain errors, parameter values will be affected, as will the predictions for other periods that depend on these calibrated parameter values (Mwakalila *et al*., 2001).

METHODOLOGY

TOPMODEL requires relatively little data for operation. Only three time-based data sets are required: rainfall, evapotranspiration (ET) and measured discharge at the catchment outlet (used in calculation of model efficiency). Daily precipitation data were available from 10 rainfall gauges located within the catchment, but data from these gauges must be reduced into one data set before the model can be run. Three methods were applied to obtain a representative rainfall data set for input into TOPMODEL. An arithmetic mean of the 10 gauges, an effective rainfall determined using a transfer function model (TFM) applying a data-based mechanistic (DBM) approach, and a weighted distribution based on the correlation between rainfall data from each gauge and observed river discharge.

Mean rainfall representation

Using the arithmetic mean, precipitation measurements from each of the 10 gauges were averaged, for each time step, to give one data set of representative rainfall depth. TOPMODEL assumed rainfall to be uniformly distributed over the entire catchment area. One deficiency in using the arithmetic mean method is that it assumes that rainfall at each gauging station has an equal proportion of impact on the catchment for every time step. In the case of a gauge located near the border, the measured rainfall at this location may be much less representative of rainfall for the entire catchment than a gauge in the centre of the catchment. Different methods exist for dividing the region spatially and assigning weights according to areas of influence (Chow *et al*., 1988).

TFM effective rainfall

Another approach involved 'calibrating' the rainfall data before using it as input for the TOPMODEL simulation. An empirically based method and a conceptually based method were essentially coupled together. A DBM approach with a bilinear power law for effective rainfall, developed by Young and Beven (1994), was applied to improve the meaningfulness of rainfall data before using it in TOPMODEL. The TFM software (Beven, 1996) is provided by and discussed in greater detail in Beven (2001).

The basic principal of the DBM approach is to relate a set of input data to a set of observed output data by allowing the data, itself, to suggest the structure of the model. The TFM uses an effective rainfall that is dependent on rainfall input and observed or estimated discharge. For calibration purposes, the observed discharge was used. Validation can be carried out most conveniently using the available TFM software and observed discharge, but by iterating the following equations, input of observed discharge can be avoided (Beven, personal communication, 2002). The mean rainfall input represents the best available estimate of rainfall. The observed or estimated discharge represents the best estimate of antecedent moisture conditions (Beven, 2001). Otherwise, the TFM is an empirical model with little physical basis in the actual catchment.

The general form of the TFM is

$$Q_t = \frac{b_0 + b_1 z^{-1} + \cdots + b_m z^{-M}}{1 - a_1 z^{-1} - a_2 z^{-2} + \cdots + a_n z^{-N}} U_{t-\delta} \tag{1}$$

Q_t is the simulated discharge, N and M define the number of a and b parameters respectively. The values for a parameters define the mean residence time in the storm hydrograph and the b parameters scale the difference between input and output for the catchment system. These are calibrated automatically, along with their associated variance, within the TFM software. The variable z

$$z = \frac{U_t}{U_{t-1}} \tag{2}$$

is known as a backward difference operator.

$$U_{t-\delta} = R_t (Q_{\mathrm{ob}})^n \tag{3}$$

defines the non-linear rainfall filter function. The effective rainfall at time t, with time delay δ, is $U_{t-\delta}$. R_t is observed rainfall, Q_{ob} is observed discharge and n controls the degree of non-linearity. A value of zero for n would indicate a linear filter function.

Using this procedure, the degree of non-linearity n for the bilinear power law algorithm was calibrated manually. For each trial n value, a range of model forms was run to determine Q_t for first-, second- and third-order model functions. The Nash and Sutcliffe (1970) R^2 efficiency index and the Young information criterion (YIC; Young, 1984) were used to evaluate the appropriateness of each model form. The YIC combines a 'goodness of fit' element with an assessment of the stability of parameter estimates. Once the optimal model form and n values were determined, the transformed rainfall data were applied in TOPMODEL. For the validation, the same parameter values and degree of non-linearity were reapplied. A schematic of the process used is shown in Figure 1. As the TFM uses a non-physically based means of simulating discharge, in some cases it was necessary to adjust the TFM effective rainfall by a conversion factor to bring the magnitude of the rainfall more in line with observations.

Correlation-weighted rainfall input

The use of correlation-weighted rainfall is more of an analysis tool than a means of generating rainfall for the purpose of river flow prediction. Unlike the TFM effective rainfall, correlation-weighting of gauges requires both rainfall and observed discharge, as storms cannot be expected to distribute rainfall over the same areas in equal quantities consistently. Its application proves that better simulation results than those determined

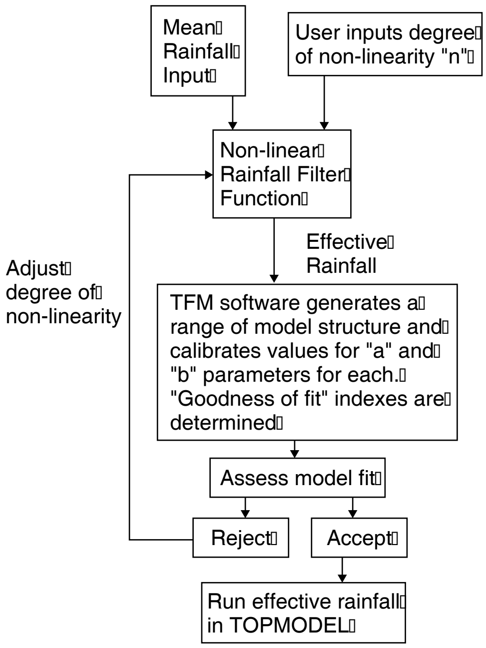


Figure 1. Schematic of TFM effective rainfall generation

using mean rainfall are possible. It also illustrates the impact of not considering spatial distribution of rainfall in river modelling and provides a means of assessing the relevance of each gauge and the TFM effective rainfall.

Weights were assigned statistically based on the correlation between measured discharge and measured rainfall at each station according to

$$\beta_{Q,R} = \frac{\mathrm{cov}(Q, R)}{\sigma_Q \sigma_R} \tag{4}$$

where covariance is defined as

$$\mathrm{cov}(Q, R) = \frac{1}{n} \sum (Q_i - \mu_Q)(R_i - \mu_R) \tag{5}$$

and the standard deviations of the discharge and rainfall data sets are

$$\sigma_Q^2 = \frac{1}{n} \sum (Q_i - \mu_Q)^2 \tag{6}$$

and

$$\sigma_R^2 = \frac{1}{n} \sum (R_i - \mu_R)^2 \tag{7}$$

respectively. The elements in each of the two data sets, Q and R, are Q_i and R_i. The means of the two data sets are μ_Q and μ_R. The number of elements in each data set is n.

As correlation factors between rainfall data at each gauge and the measured discharge showed considerable variation, it was clear that all the gauges did not carry an equal significance to the representative rainfall over the study area. To obtain a more representative estimate of rainfall, gauges with the highest correlation factors were weighted as follows:

$$W_g = \frac{\beta_g}{\sum \beta_i} \tag{8}$$

If more than one gauge was used, then the rainfall data for each time step was generated by summing the products of the respective weighting factor and gauge data for each included rainfall gauge. Figure 2 shows the position of rainfall gauges.

Data limitations

The two proposed methods of improving rainfall representation over mean rainfall were tested using a calibration and cross-validation approach. There were two main issues that prevented the use of a more conventional approach. As the version of TOPMODEL used in the study was not equipped with a means of handling snowmelt, snow and ice conditions during winter months prevented the data sets from being run consecutively. Apart from this, there was no desire to add additional complexity to the already difficult task of applying TOPMODEL to a large, dry region. The second issue was a lack of detailed ET data. Application of TOPMODEL was found to be sensitive to ET input in this large, semi-arid region. Only the 1989 and 1990 data sets included daily, observed ET. For the years 1987, 1986, 1985 and 1981 only ET data extrapolated from monthly mean values were available.

In an attempt to compensate for these inadequacies, calibration was conducted on the more reliable 1989 and 1990 data sets separately with each of the three rainfall input types. Mean rainfall for the 6 years considered varied between 320 and 580 mm. The 1990 data set represented a wetter year, with 540 mm mean measured rainfall, whereas 1989 was a drier year with 370 mm. Parameter sets determined from the 1989 calibration period were validated against each of the other 5 years. Likewise, parameters from the 1990 calibration period were validated against the years 1989, 1987, 1986, 1985 and 1981.

Only daily input data were available. As discussed below, climatic and hydrological conditions of the Banqiao sub-catchment suggest that data at a much smaller time step would be more appropriate.

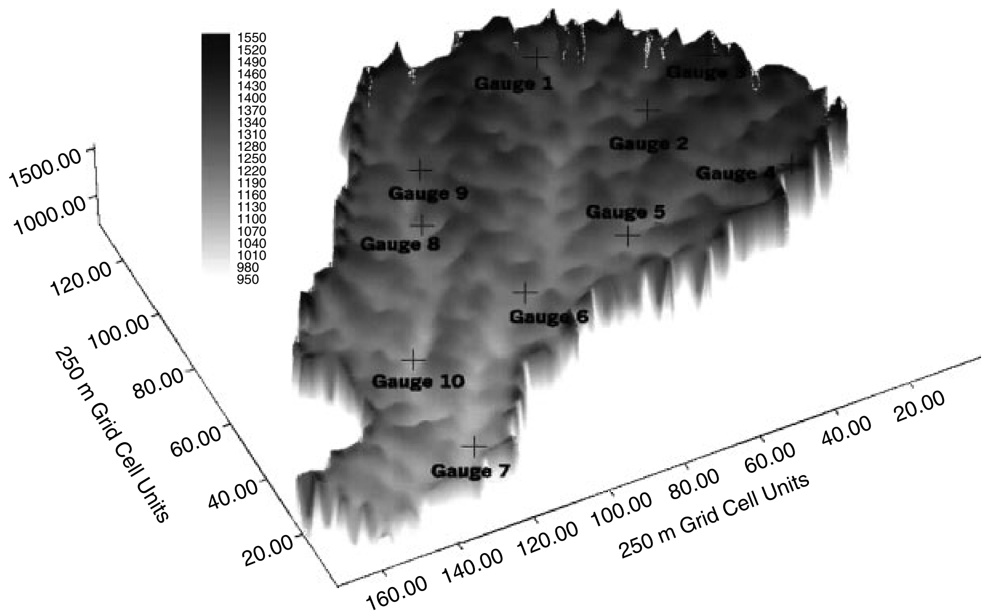


Figure 2. Digital elevation map of Banqiao sub-catchment showing positions of rainfall gauges

RESULTS AND DISCUSSION

Model calibration and validation

Table I shows the calibration results from the 1989 and 1990 calibration periods using TOPMODEL and the TFM. For both periods, using the correlation-weighted and TFM effective rainfall data improved TOPMODEL efficiency over the use of mean rainfall.

Although the validation efficiencies generally lagged those seen during calibration, 90% of TOPMODEL validation runs using TFM effective rainfall and 60% of those using correlation-weighted rainfall exceeded runs using mean rainfall. Table II shows validation results for runs using TOPMODEL and the TFM by itself.

Typically, the Banqiao sub-catchment receives the most rainfall during a short period of the year and the number of large peak discharge events is usually few. Since the total area of the sub-catchment is large, major peak events can be linked to heavier rainfall over a limited portion of the sub-catchment. For the years included in this study, it was found that the number of major peak events was directly related to the number of gauges exhibiting high correlation factors. In general, one gauge recorded most of the rainfall input that resulted in each of the hydrograph peaks. The exceptionally poor performance of the 1986 data set can likely be attributed to large volumes of snowmelt runoff preceeding the first step in the data series. This resulted in base flow being calculated as much higher than reality. This larger volume of water in the beginning of the period receded during the first 2 months of the data set. Under other data sets and the calibration years, this type of recession was not observed; hence, the parameters were unable to reflect this type of behaviour.

In comparing validation results for 1985, 1987 and 1989, both TOPMODEL and the TFM failed to simulate the highest peak events. For TOPMODEL, both the 1990 and 1989 parameter sets applied to 1985 and 1987 validation periods generated nearly the same output. However, the 1990 parameter set was notably better for the 1981 validation. It is likely that these peaks are the result of high-intensity rain over a short period of

Table I. Model efficiency represented by R^2 for 1989 and 1990 calibrations of TOPMODEL and the TFM

Calibration	Rainfall input		
	TFM	Weighted	Mean
TOPMODEL (1989)	0·592	0·397	0·380
TOPMODEL (1990)	0·835	0·757	0·312
TFM (1989)	0·440	N/A	N/A
TFM (1990)	0·803	N/A	N/A

Table II. Validation and cross-validation of 1989 and 1990 parameter sets using TOPMODEL with different rainfall input types; validation of transfer function model for 1989 and 1990 calibration parameter sets using the same degree of non-linearity in the effective rainfall. Results are presented as R^2 values representing the degree of agreement with observed discharge

Parameter set	Validation year					
	1990	1989	1987	1986	1985	1981
TFM 1990	N/A	0·278	0·189	−3·21	0·280	0·873
Weighted 1990	N/A	0·096	0·024	−1·564	0·213	0·647
Mean 1990	N/A	−0·313	0·048	−5·761	0·077	0·637
TFM 1989	0·508	N/A	0·232	−1·480	0·208	0·551
Weighted 1989	0·427	N/A	0·005	−1·121	0·179	0·385
Mean 1989	0·061	N/A	0·015	−1·101	0·135	0·397
TFM Model 1989	0·715	N/A	0·039	0·154	0·268	0·723
TFM Model 1990	N/A	0·330	0·035	0·073	0·233	0·816

time, since storms of similar yield produced much lower peaks in other parts of the data sets. It is impossible to simulate the occurrence of flash floods, such as these, without the use of a much more refined time step than the 24 h data available for this study. In a study of erosion and runoff by Cantón *et al*. (2001), a badland environment was studied as a series of microcatchments using a 20 s time step to capture the effects of variable rainfall intensity.

Table III shows that when considering all 6 years included in the study, TFM effective rainfall consistently demonstrated a higher correlation with stream discharge than either the mean rainfall or correlation-weighted rainfall. Likewise, correlation-weighted rainfall was consistently more strongly correlated than mean rainfall.

TFM effective rainfall

Using the TFM allowed for adjustment of input rainfall data sets to determine which was able to produce the best model efficiency after transformation. The calibrated, transformed data was found to produce better model efficiency over non-transformed data during the 1989 and 1990 calibration periods and the majority of validation runs. Figures 3 and 4 compare the TOPMODEL simulations using mean rainfall and TFM effective rainfall against observed discharge. The TFM was also valuable in assessing the appropriateness of the TOPMODEL structure. The basis of the approach is that the model structure is determined by the data. In application, a first-order model was found to be the most appropriate structure in both the 1989 and 1990 calibrations, supporting the TOPMODEL assumption. Referring to Equation (1), the fitted transfer function had values for both N and $M = 1$, meaning one a and one b parameter. The time delay for the function was optimized at zero. The n for the bilinear power law, used in calculating the effective rainfall, was calibrated manually to 0·54 for the 1990 data set and 0·44 for the 1989 data set using mean rainfall as the base input for the function.

In general, the transfer function model tends to provide a reasonable representation of peaks (with the exception of those resulting from flash flooding), but an underestimation of base flow. However, it is also limited by the mean rainfall input. After obtaining the best possible results with the TFM approach, the effective rainfall optimized for the TFM was applied as input rainfall in TOPMODEL. TOPMODEL was able to improve upon this output with a more realistic base flow simulation. Figures 3 and 4 show the validation results applying TFM effective rainfall in TOPMODEL using the 1989 and 1990 parameter sets respectively.

Table III. Correlation of rainfall with observed stream discharge. Values in bold indicate the highest correlation factors for each year. These gauges were included in the calculation of correlation-weighted rainfall

	Correlation against observed discharge					
	1990	1989	1987	1986	1985	1981
Gauge 1	0·175	0·095	−0·009	**0.322**	0·186	0·381
Gauge 2	0·361	0·206	0·006	0·239	0·150	0·451
Gauge 3	0·477	**0.274**	−0·018	0·048	0·185	0·349
Gauge 4	0·441	0·052	**0.206**	0·087	0·257	**0.772**
Gauge 5	**0.792**	**0.229**	−0·021	0·188	0·166	0·354
Gauge 6	0·371	0·170	−0·013	0·193	0·145	0·575
Gauge 7	0·177	0·161	0·014	0·263	**0.425**	0·614
Gauge 8	0·052	**0.235**	−0·017	**0.324**	0·192	0·639
Gauge 9	0·290	**0.271**	−0·022	0·092	0·135	0·657
Gauge 10	0·204	0·148	−0·017	0·120	0·172	0·659
TFM rain $n = 0·44$	0·852	0·485	0·292	0·476	0·459	0·910
TFM rain $n = 0·54$	0·881	0·522	0·439	0·523	0·505	0·910
Weighted	0·792	0·300	0·206	0·345	0·425	0·772
Mean rain	0·653	0·227	0·014	0·203	0·231	0·572

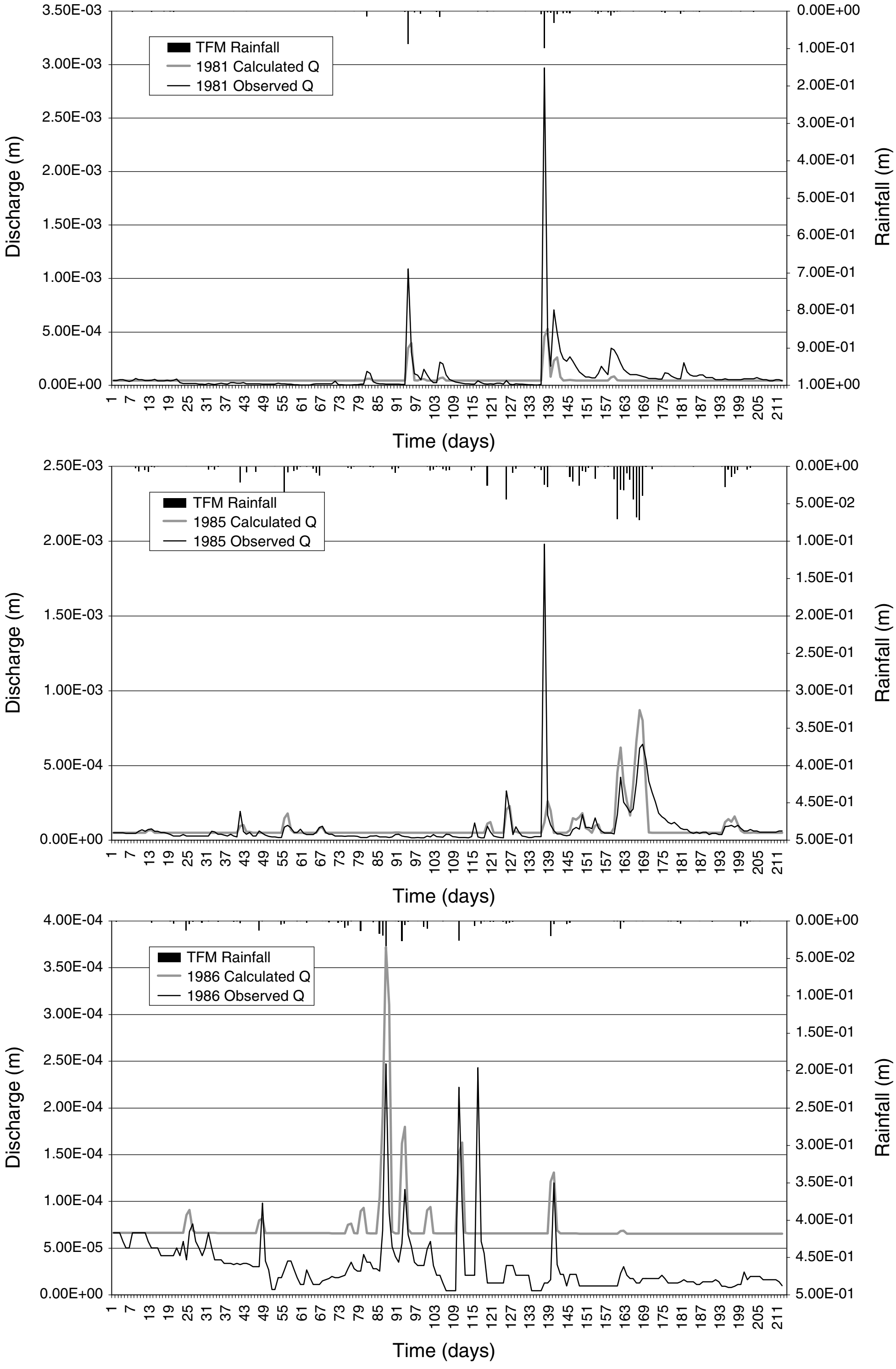
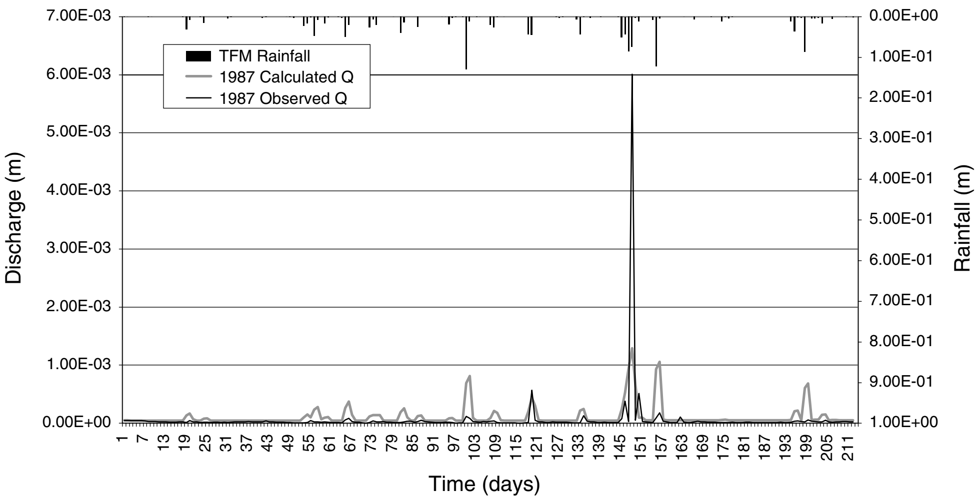


Figure 3. Validation results for 1989 calibration parameter sets



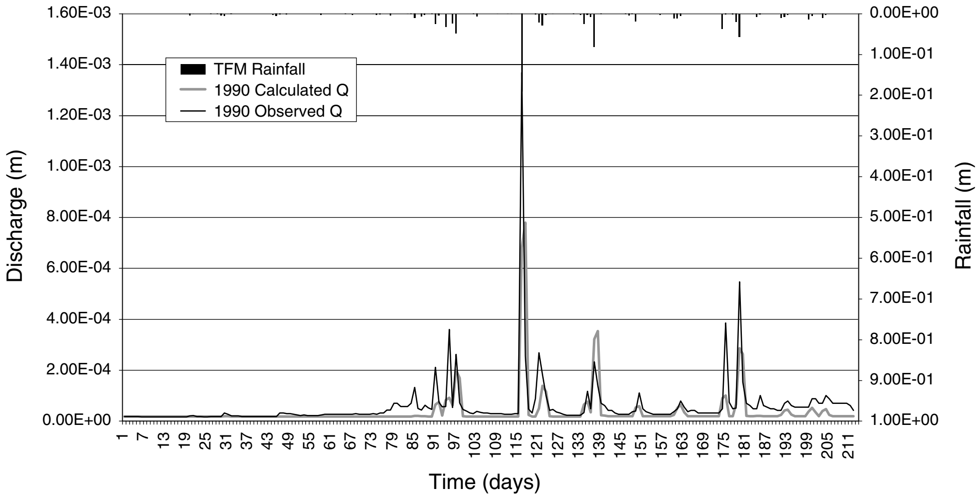


Figure 3. (*Continued*)

Correlation-weighted rainfall data

Considering the 1990 data set (Table IV), rainfall measured at Gauge 5 was shown to have the highest correlation with stream discharge when the entire calibration period is considered. For further analysis, the calibration period was divided into three subsets representing dry, transition and wet periods for the catchment. The main objective in segregating the data set was to isolate the highest peak discharge occurring on day 116 while still leaving adequate time before and after the peak for the model to stabilize. The averaged rainfall data set was consistently shown to have a lower correlation to discharge than the data from Gauge 5, and also for Gauge 4 in the case of the wet period.

When applying an arithmetic mean, all components are given equal weight, including those with poor or negative correlation to discharge. The better relationship between the Gauge-5 data and observed discharge was not adequately represented within the mean rainfall data. Although data from individual gauges was more representative of rainfall for the entire catchment, using a mean rainfall does not give these gauges enough weight to produce a good representation of rainfall for the catchment. The net effect is that the mean rainfall determined from 10 gauges provides a poorer representation of the discharge-inducing rainfall than use of

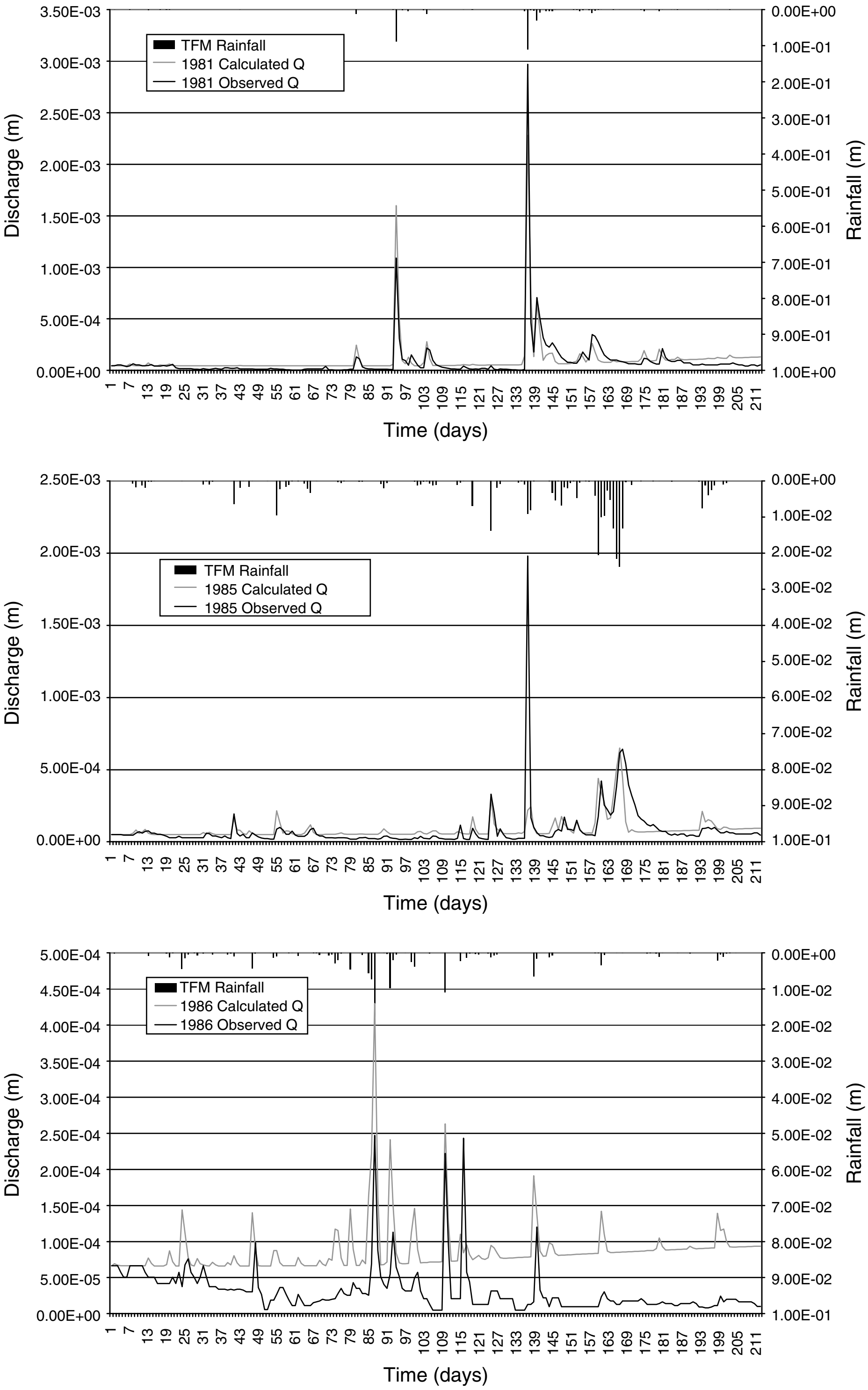


Figure 4. Validation results for 1990 calibration parameter sets

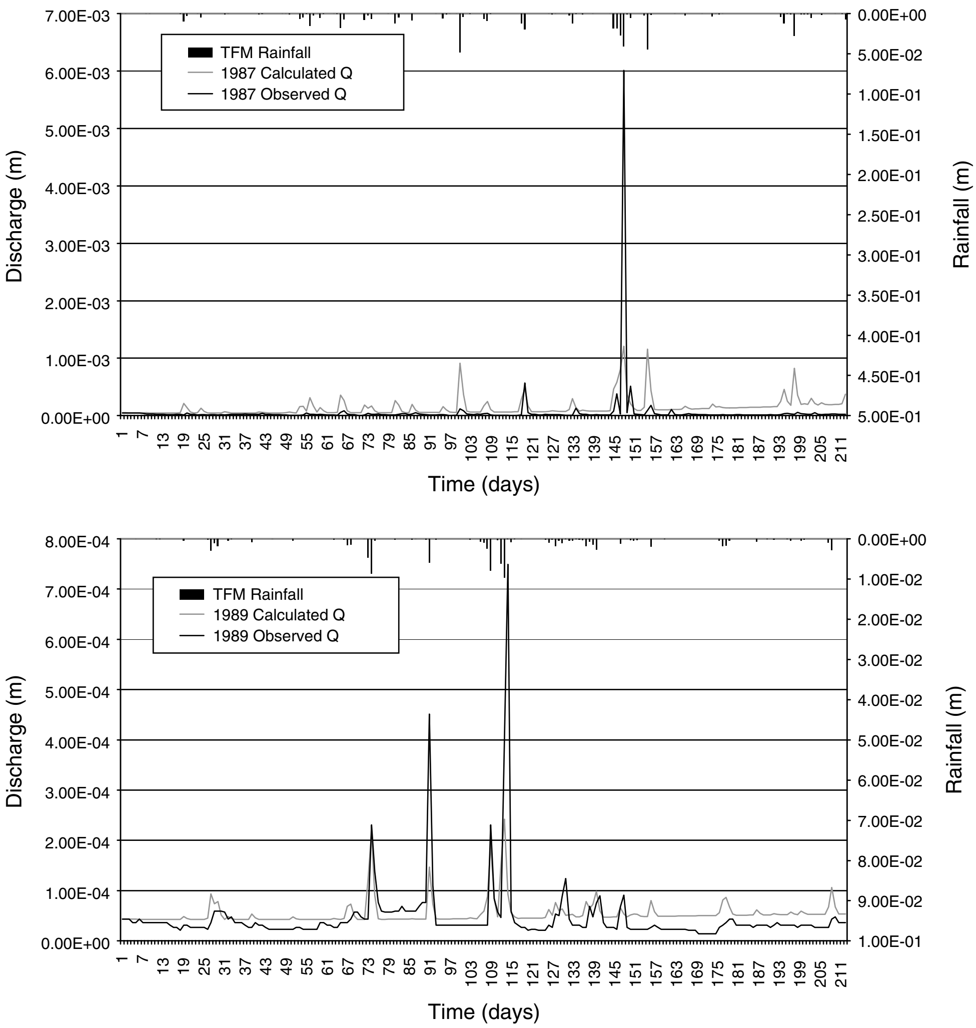


Figure 4. (*Continued*)

just one gauge or of assigning weights to measured rainfall from multiple gauges based on relative correlation with discharge.

The rainfall data for day 116 contained significant deviation between the measurements from each station. Gauge 5 reported 153·3 mm of rainfall on that day, whereas the other nine gauges reported between 0 and 51·2 mm. Therefore, using a mean rainfall for this day gave only 35·0 mm of rainfall input to the catchment. As this was not enough to produce the peak discharge that was observed, R^2 was optimized at only 0·312.

When relating the rainfall representation to model efficiency, the event on day 116 of the calibration data set demonstrates how significant rainfall input is to model efficiency. In calibrating TOPMODEL for this data set, the peak on day 116 was found to be a determining factor for the R^2 efficiency test of Nash and Sutcliffe (1970). Because this peak was so much higher than other events, reasonable model efficiency could only be reached if this peak was simulated adequately. It could be argued that the R^2 efficiency test is biased toward high peaks in a data set consisting primarily of much lower peaks and base flows. In using automatic calibration, with R^2 as the objective function, parameter sets are forced toward values that favour the highest peak events over the rest of the data set. In a wetter study area, with peak discharges exhibiting lower relative

Table IV. Correlation between measured rainfall at gauging stations and observed stream discharge for 1990

	Correlation against observed discharge			
	Full	Dry	Transition	Wet
Gauge 1	0·175	0·041	0·259	0·132
Gauge 2	0·361	−0·069	0·530	0·190
Gauge 3	0·477	0·027	0·734	0·205
Gauge 4	0·441	−0·174	0·634	0·379
Gauge 5	0·792	0·205	0·911	0·272
Gauge 6	0·371	−0·101	0·535	0·188
Gauge 7	0·177	−0·022	0·261	0·155
Gauge 8	0·052	0·024	0·007	0·077
Gauge 9	0·290	−0·093	0·406	0·181
Gauge 10	0·204	−0·070	0·346	0·159
TFM rain	0·881	0·218	0·946	0·589
Mean rain	0·653	−0·028	0·667	0·221

magnitude and greater temporal uniformity, R^2 produces a less biased assessment of agreement between observed and calculated discharge. Considering this tendency, it seems reasonable that the greatest impact to the rainfall data sets using the TFM filter and correlation-weighting is to the rainfall that generates the highest peaks in the time period. However, in the case of high-intensity storm events, neither of these processes was consistently effective at such a large time step.

CONCLUSIONS

When considering all 6 years included in the study, TFM effective rainfall consistently demonstrated a higher correlation with stream discharge than either the mean rainfall or correlation-weighted rainfall. Likewise, correlation-weighted rainfall was consistently more strongly correlated than mean rainfall. In validation runs of TOPMODEL, compared with the use of mean rainfall, 90% of those runs employing TFM effective rainfall produced higher R^2 efficiency. Using correlation-weighted rainfall gave better agreement with observed discharge than mean rainfall for 60% of validation runs.

As this study found the R^2 efficiency index to be highly sensitive to the small number of high peaks in the data set, the most significant error is associated with these peaks. The two main causes for poor agreement at these points are:

1. Difficulties in adequately representing spatial distribution of rainfall throughout the catchment.
2. Coarse temporal resolution of the input, which makes the simulation of sub-time-step events, like flash flooding, difficult, if not impossible.

As model calibration favours peak events at the cost of lower flow events, parameter sets tend to be skewed toward these large events at the cost of better predictions during the rest of the data set. Since the temporal resolution of the data is too coarse to show high-intensity events, and adequate spatial representation of discharge-generating rainfall is difficult over this large region, high peak events were often missed as well.

There are other, less significant, contributing factors to the variation in model performance over the years considered. Errors in data, either in those years showing poor performance or in those years used to calibrate parameters, are one possible source. Errors in data collection can have compounding effects in modelling applications in arid regions. In the study of another semi-arid catchment by Mwakalila *et al*. (2001), errors in the input were found to be dominated by peaks during the wet seasons, but the magnitude of errors during dry periods were comparatively smaller.

The selection of the optimized parameter set may also have led to poorer performance during validation. Automatic calibration generated hundreds of parameter sets with similar efficiency. Selection of a single parameter set from those exhibiting the highest efficiency was done arbitrarily. Beven (2001) suggests the use of a concept known as generalized likelihood uncertainty estimation. The methodology is based on the pretence that the quality of output from a model is not a function of individual parameter values, but of a set of parameter values acting together. The methodology uses multiple model runs to plot a probability density for each model parameter that can be used to assess the sensitivity of parameter values. Although the focus of this study was to evaluate the use of pre-processed rainfall to improve model efficiency, statistical analyses of the sensitivity of parameter sets could merit further study. However, comparison of validation results for the TFM, alone, also show poorer results for the same years where poor validation results were obtained with TOPMODEL. Since the TFM used fewer parameter values with no parallel conceptual basis to those used in TOPMODEL, selection of parameter sets from those with the highest efficiency ratings is not likely the largest source of error in this study.

Changes in land use and surface cover could also create inconsistencies between hydrological conditions present during the calibration years and those used in validation, as could cycles in weather patterns.

The study showed gains in model efficiency through the practice of pre-processing rainfall input data using correlation weighting and transfer function effective rainfall. Although consistent improvements were seen in this study, limitations in the data prevented the reliable simulation of the catchment. Further research might apply a similar methodology using more refined, longer continuous data sets.

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